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P. Mahalakshmi, Mathanraj V, S. Satish Kumar
SETHU INSTITUTE OF TECHNOLOGY, SRM INSTITUTE OF SCIENCE AND TECHNOLOGY, AMET UNIVERSITY

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[1]P. Mahalakshmi, Associate Professor, Department of Electronics and Communication Engineering, Sethu Institute of Technology, Virudhunagar – 626115. maha.lakshmijun26@gmail.com

[2]Mathanraj V, Associate Professor, Department of Mechanical Engineering, SRM Institute of Science and Technology, kattankulathur -603203. matharv@srmist.edu.in

[3]S. Satish Kumar, Associate Professor, Department of Marine Engineering, AMET University, 135 East Coast Road, Kanathur, Chennai – 603112. satishkumarjec@gmail.com

Abstract

The rapid evolution of healthcare technologies has spurred a shift towards continuous, real-time monitoring of patients' vital signs, creating an urgent need for advanced anomaly detection systems. This chapter explores the application of deep learning models, particularly Autoencoders and Long Short-Term Memory (LSTM) networks, in the detection of anomalies within vital sign data streams. By leveraging the unique strengths of these models, healthcare systems can effectively identify subtle deviations in patient health metrics, such as heart rate, blood pressure, and respiratory rate, that may indicate deteriorating conditions. Autoencoders, with their ability to learn normal patterns from unlabeled data, and LSTMs, designed to capture long-term temporal dependencies in time-series data, are presented as powerful tools for addressing the challenges associated with real-time anomaly detection in clinical settings. Through case studies and practical applications, this chapter highlights the significant potential of these deep learning techniques in improving patient outcomes through early intervention, enhanced prediction of acute events, and more personalized care strategies. The growing integration of these models in wearable devices, mobile health applications, and remote patient monitoring systems is also examined, emphasizing their role in facilitating proactive and patient-centered healthcare. Key challenges related to data noise, missing values, and scalability are addressed, alongside strategies for overcoming these limitations in real-world healthcare environments. This chapter contributes valuable insights into the transformative potential of machine learning in modern healthcare, providing a foundation for future research and development in anomaly detection, health monitoring, and predictive healthcare analytics.

Keywords: Anomaly Detection, Autoencoders, LSTM Networks, Vital Signs, Healthcare Analytics, Real-Time Monitoring.

Introduction

The healthcare industry is undergoing a significant transformation, driven by advancements in technology that enable real-time, continuous monitoring of patients’ vital signs [1]. Healthcare providers relied on periodic check-ups to assess patients' health status [2]. However, with the rise of wearable devices, remote health sensors, and mobile health applications, a shift toward continuous health data collection has been established [3]. This transformation offers significant potential to detect health abnormalities early, providing the opportunity for timely intervention and proactive management of medical conditions [4]. With these advancements, patients no longer need to wait for scheduled visits to healthcare facilities for a comprehensive health assessment. Instead, a wealth of real-time data is available that can provide insights into an individual's health on a constant basis [5].

One of the main challenges associated with continuous health monitoring is the sheer volume and complexity of data generated by these systems [6]. Vital signs such as heart rate, blood pressure, respiratory rate, and body temperature are continuously recorded, resulting in vast amounts of data that need to be analyzed efficiently [7]. The ability to detect anomalies in this data is critical, as even minor deviations from normal ranges can indicate the early stages of a potentially severe health issue [8]. Anomaly detection, therefore, plays a pivotal role in real-time health monitoring systems, helping healthcare providers identify concerning trends before they escalate into life-threatening conditions [9]. For instance, a sudden drop in blood oxygen saturation or an abnormal increase in heart rate could signal the onset of respiratory failure, sepsis, or other acute medical conditions that require immediate attention [10].

The growing reliance on machine learning (ML) models for anomaly detection in healthcare has paved the way for more accurate, scalable, and automated approaches to managing patient health data [11]. Traditional methods, which rely on predefined thresholds or manual interventions, often struggle to detect subtle anomalies, particularly in the case of patients with complex or chronic health conditions [12]. Machine learning, and particularly deep learning techniques, has emerged as a powerful tool for addressing these challenges [13]. Models such as Autoencoders and Long Short-Term Memory (LSTM) networks are designed to process vast amounts of time-series data, automatically identifying abnormal patterns without the need for explicit human intervention [14]. These models are well-equipped to handle the intricacies of healthcare data, which often exhibits complex temporal dependencies and non-linear relationships [15].